POSITION ESTIMATION OF A CAR-LIKE MOBILE ROBOT USING A GYROSCOPE AND DISTURBANCE CONDITIONS

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Abstract: In this paper, we propose an improved dead-reckoning method for estimating current position and orientation of the mobile robot using wheel-rotation sensors and a gyroscope. Up to now, pre-identified model is usually used to get more accurate posture from the gyroscope. However, this model can lose its accuracy during the operation including temperature change. To overcome this limitation, a real-time identification method based on disturbance condition is proposed so that the gyroscope information can keep its accuracy. The disturbance condition can determine whether there are lateral or longitudinal disturbances or not. Experimental results are presented, which show the effectiveness of our method in contrast with conventional ones.

Keywords: Posture estimation, Odometry, Uncertain parameters of a gyroscope, Disturbance Condition, Real-time identification.

1 INTRODUCTION

The most-widely used dead reckoning method is odometry which calculates current position of a wheeled mobile robot(WMR) by integrating the wheel velocity. However, due to the unpredictable slippage and road irregularity, when these kinds of disturbances occur, the method using odometry does not guarantee accurate position of the mobile robots any more. Recently, by virtue of the development of low-cost gyroscopes, the usage of gyros is growing up rapidly for dead reckoning system of the mobile robot. In contrast to odometry, slippage and road irregularity have little influence on the output of the gyroscope, but this can be deviated from real value due to the characteristics of the built-in signal amplifier in gyroscope. In order to get a precise orientation information from a gyroscope, we need accurate identification. To do this, we need a proper output model of the gyroscope. Basically, the output of gyroscope is a voltage signal, so we must know the bias voltage and scaling factor which converts voltage to angular velocity. Up to now, most of researches focus on the identification of bias voltage which varies as time goes [1, 3]. However, the scaling factor which will be defined in the next section can cause inaccurate angular velocity when a mobile robot is turning. This is the first motivation of this paper.

To find out the uncertain parameter, we developed a on-line identification algorithm because the characteristics of gyroscope can be changed by thermal condition. This identification, however, should be done with precise information of angular velocity. This means that the identification based on wrong odeometry data can result in wrong identification result. We need some criterion to determine whether the odometry data is reliable or not. In fact, Maeyama et al.[4] proposed on-line identification algorithm which estimates bias voltage of a gyroscope using the property that the angular rate measured by the gyroscope and odometry are almost the same if there is no disturbance such as slippage [2]. However, in order that this decision rule properly works, initial uncertainty in gyroscope must be sufficiently small. This is the second motivation of this paper.

In this paper, in order to get precise angular velocity of a WMR, we propose a disturbance condition which can determine whether the current odometry is right or not using the additional sensor in the steering wheel which is already built in the WMR. Section 2 describes the characteristics of gyroscope, section 3 and 4 describe the mobile robot used in this paper and the proposed algorithm. Results are shown in section 5 and conclusion follows.

2 CHARACTERISTICS OF GYROSCOPE

We used gyroscope Gyrostar ENV-05A manufactured by Murata. The detail specification of gyroscope is shown in Table 1. These parameters are usually given by the manufacturer, however, because a typical low-cost gyroscope has a built-in signal amplifier, the above parameters are influenced by the thermal condition. As you can see in this table, scaling factor as well as bias voltage have variations. Till now, conventional method uses scaling factor as a mean value of this table which varies ±10 percent during operation. To convert the output of a gyroscope, we will estimate the exact values of the followings.

- *Bias voltage* which indicates the voltage when gyroscope stands stationary.
- *Scaling factor* which represents the ratio between signal output and angular velocity.

In order to cancel out the effects of gyroscope's output variation, Barshan and Durrant-Whyte[1] proposed the following error model:

$$\dot{\alpha} = \dot{\alpha}_m + \epsilon \quad (1)$$

$$\epsilon = C_1(1 - e^{-t/T}) + C_2, \quad (2)$$

where $\dot{\alpha}$ is the real angular velocity, $\dot{\alpha}_m$ is the measured angular velocity which is obtained from voltage output multiplied by nominal scaling factor, and ϵ is the drift with parameters C_1, C_2, and T. However, because this model is only for *drift*, it is not adequate for the case when the scaling factor is uncertain. To obtain more precise information from gyroscope, this value must be accurately identified. For this reason, we introduce a new parameter - *Scaling Correction Factor*, which modifies the nominal scaling factor. Then the model of gyroscope is formulated as the following equation.

$$\dot{\alpha} = C\dot{\alpha}_m + D \quad (3)$$

where $\dot{\alpha}_m$ is the measured angular velocity by using nominal parameters, C is scaling correction factor that modifies the nominal conversion factor, and D is the conventional drift value. The main gyroscope identification scheme will be described in section 4.

3 WHEELED MOBILE ROBOT : PosTur-I

The picture of our mobile robot, *PosTur-I*, is shown in Figure 1. Our mobile robot employs a single front steering wheel and two independent-driving wheels at the rear side. This three-point triangular configuration ensures good stability and enough traction force. PosTur-I has three motors, one is for the steering mechanism, the others are for driving rear wheels.

To estimate the position and orientation of PosTur-I, in addition to three wheel encoders which are equipped for servo control of motors, we use a gyroscope and an encoder at front wheel to measure the front wheel rotation. The overall system structure of our mobile robot is briefly shown in Figure 2.

Table 1: Spec.of gyroscope, Gyrostar ENV-5A

Item	Description
Type	Piezoelectric
Dimension	25(W)X25(D)X57.5(H) mm
Weight	less than 45g
Bias Voltage	2.20-2.80 V
Scaling Factor	20.4-24.0 mV/(deg/sec)
Maximum Rate	90 deg/sec
Power	12VDC 15mA

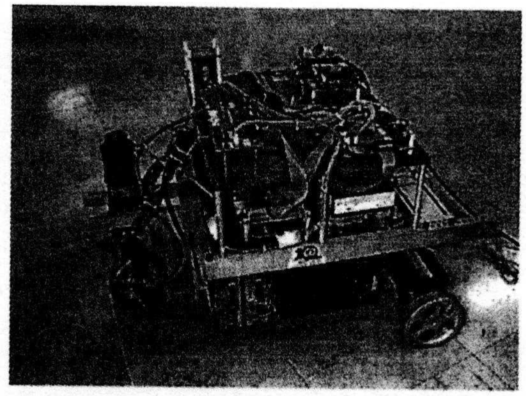

Figure 1: Wheeled mobile robot, *PosTur-I*

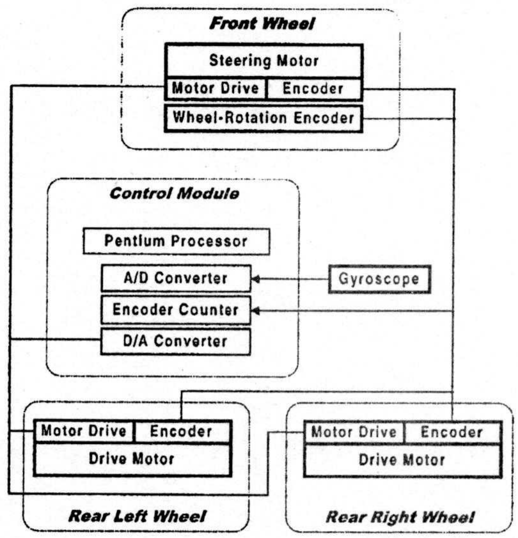

Figure 2: System configuration of mobile robot, *PosTur-I*

4 DEAD RECKONING ALGORITHM USING ADDITIONAL SENSORS

Conventionally, to obtain the odometry from the kinematics of wheeled mobile robot(WMR), the following is assumed.

- No disturbance such as slippage at the wheels occurs.
- The Mobile robot moves in a 2D plane.

However, in real applications, because these assumptions are frequently broken, odometry loses its accuracy. In this section, firstly, we derive a generalized kinematic constraints which include the behavior of disturbance at the wheels, and also develop a decision rule to check whether disturbance occurs at the wheels - called *disturbance condition.* Finally, we build a dead-reckoning algorithm which can perform both position estimation and gyroscope identification simultaneously.

Kinematic Constraints and Odometry

All disturbances at the wheel can be divided into two types: lateral and longitudinal disturbance (usually called skid and slip, respectively), which are shown in Figure 3. The configuration and dimensions of the mobile robot are also described in Figure 4. The kinematic constraints including disturbances can be derived as follows.

$$\begin{aligned}\dot{x}_f &= \dot{x} - L\dot{\alpha}\sin\alpha \\ &= (\dot{s}_f + \dot{d}_f)\cos(\alpha+\phi) - \dot{l}_f \sin(\alpha+\phi) \quad (4)\\ \dot{y}_f &= \dot{y} + L\dot{\alpha}\cos\alpha \\ &= (\dot{s}_f + \dot{d}_f)\sin(\alpha+\phi) + \dot{l}_f \cos(\alpha+\phi) \quad (5)\\ \dot{x}_r &= \dot{x} + \tfrac{T}{2}\dot{\alpha}\cos\alpha \\ &= (\dot{s}_r + \dot{d}_r)\cos\alpha - \dot{l}_r \sin\alpha \quad (6)\\ \dot{y}_r &= \dot{y} + \tfrac{T}{2}\dot{\alpha}\sin\alpha \\ &= (\dot{s}_r + \dot{d}_r)\sin\alpha + \dot{l}_r \cos\alpha \quad (7)\\ \dot{x}_l &= \dot{x} - \tfrac{T}{2}\dot{\alpha}\cos\alpha \\ &= (\dot{s}_l + \dot{d}_l)\cos\alpha - \dot{l}_l \sin\alpha \quad (8)\\ \dot{y}_l &= \dot{y} - \tfrac{T}{2}\dot{\alpha}\sin\alpha \\ &= (\dot{s}_l + \dot{d}_l)\sin\alpha + \dot{l}_l \cos\alpha \quad (9)\end{aligned}$$

where x, y and α are the position and orientation of the mobile robot, ϕ is the steering angle of the front wheel, $\dot{s}$ denotes the velocity of each wheel, d and l are the longitudinal and lateral disturbance of each wheel, and subscript f, r, and l represent front wheel, rear-right wheel, and rear-left wheel, respectively.

To get the position information from odometry, the position and orientation of the mobile robot must be expressed by the variables of wheel state $(s,\ \phi)$, which are measured from wheel encoders. If no disturbance occurs, the position and orientation can be estimated with the following equations.

$$\begin{aligned}\dot{x} &= \tfrac{1}{2}(\dot{s}_r + \dot{s}_l)\cos\alpha \quad (10)\\ \dot{y} &= \tfrac{1}{2}(\dot{s}_r + \dot{s}_l)\sin\alpha \quad (11)\\ \dot{\alpha} &= \tfrac{1}{T}(\dot{s}_r - \dot{s}_l) \quad (12)\end{aligned}$$

It is obvious that this result is valid only for the case where there is no disturbance at each wheel, therefore, when disturbances occur, the odometry loses its accuracy.

Disturbance Condition

If we can find a condition which can determine whether there exists a disturbance (such as slippage) at the wheels or not, it can be used as a decision rule which tells us whether odometry is good or not. The main idea for building disturbance condition is: If the number of wheel configuration coordinates is greater than the degrees of freedom of a WMR, there exists at least one relation which constrains the behavior of each wheel when there exists no disturbance at the wheels[5]. This is the reason why we use an additional encoder at the front wheel. In the case of a car-like WMR such as PosTur-I, which has two degrees of freedom, the wheel configuration coordinates can be defined as following four variables:

- rotation of rear-right wheel : s_r
- rotation of rear-left wheel : s_l
- rotation of front wheel : s_f
- steering angle (orientation of front wheel): ϕ

In PosTur-I, s_r, s_l, and ϕ can be measured from the 3 motors and an additional sensor to measure the rotation of the front wheel(s_f) is attached. We assume that s_r, s_l, and ϕ are commonly measurable, and we derive two disturbance conditions according to the availability of additional information for s_f.

CASE 1: When s_f is available.
By eliminating the position variables(x, y, and α) from the kinematic constraints, we obtain the following relations.

$$D\dot{d} = S\dot{s}, \quad (13)$$

where

$$\begin{aligned}\dot{d} &= [\ \dot{d}_f\ \ \dot{d}_r\ \ \dot{d}_l\ \ \dot{l}_f\ \ \dot{l}_r\ ]^T,\\ \dot{s} &= [\ \dot{s}_f\ \ \dot{s}_r\ \ \dot{s}_l\ ]^T,\\ D &= \begin{bmatrix}\cos\phi & -\frac{1}{2} & -\frac{1}{2} & -\sin\phi & 0\\ \sin\phi & -\frac{L}{T} & \frac{L}{T} & \cos\phi & -1\end{bmatrix},\\ S &= \begin{bmatrix}-\cos\phi & \frac{1}{2} & \frac{1}{2}\\ -\sin\phi & \frac{L}{T} & -\frac{L}{T}\end{bmatrix}.\end{aligned}$$

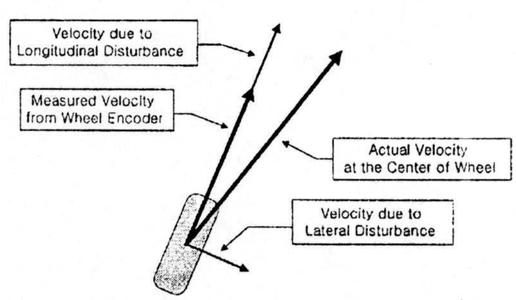

Figure 3: Disturbance model of a wheel

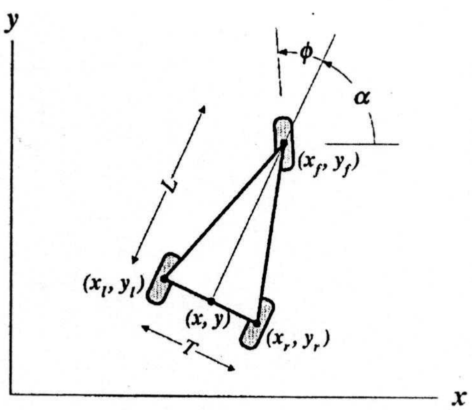

Figure 4: Configuration of a car-like mobile robot

Because the lateral disturbances are the same at the rear wheels, an obvious relation that $\dot{l}_r = \dot{l}_l$ is used in the elimination procedure. The physical meaning of this equation is that when the right-hand side of Eq.(13) is not equal to zero, at least one of disturbance variables at the left-hand side has to have a non-zero value. Note that the right hand side of Eq.(13) is solely the function of measurable values with kinematic constraint. Therefore a disturbance condition can be stated as follows:

Disturbance Condition 1 *If $||S\dot{s}||$ has a non-zero value, there exist a disturbance at the wheels.*

CASE 2: ***When s_f is not available.***

If the rotational speed of the front wheel $\dot{s}_f$ is not available, we cannot use the disturbance condition in Case 1. However, the following equation can be obtained by eliminating $\dot{s}_f$ from Eq.(13):

$$\begin{aligned}&(\tfrac{1}{2}\sin\phi - \tfrac{L}{T}\cos\phi)\dot{d}_r + (\tfrac{1}{2}\sin\phi + \tfrac{L}{T}\cos\phi)\dot{d}_l \\ &+ \dot{l}_f - \dot{l}_r\cos\phi \qquad (14)\\ &= -(\tfrac{1}{2}\sin\phi - \tfrac{L}{T}\cos\phi)\dot{s}_r - (\tfrac{1}{2}\sin\phi + \tfrac{L}{T}\cos\phi)\dot{s}_l\end{aligned}$$

By a similar reasoning to that of the CASE 1, we can get the following condition.

Disturbance Condition 2 *If the left-hand side of Eq.(14) is not zero, there exist a disturbance at the wheels.*

Of course we need to define some threshold value to numerically define *zero* using measured signal. Our experience says that when there is a disturbance, we can easily detect the existence of the disturbances using the above conditions. The threshold value used here is 0.014.

Real-time Gyroscope Identification (RGI)

So far, many researchers used off-line identification methods to find out the accurate characteristics of gyroscopes. However, because the characteristics of gyroscopes can vary when the ambient temperature changes, pre-identification of gyroscope can lose its accuracy. For this reason, we use a real-time identification algorithm.

In this paper, the recursive least square algorithm is used to find out the uncertain parameters of the gyroscope, which can track the varying parameters with a forgetting factor [6]. The following is our identification algorithm.

- Parametric Model of the Gyroscope

$$\begin{aligned}\dot{\alpha}(t) &= C\dot{\alpha}_m(t) + D \qquad (15)\\ &= \begin{bmatrix}\dot{\alpha}_m(t)\\ 1\end{bmatrix}\begin{bmatrix} C & D\end{bmatrix} \qquad (16)\\ &\triangleq \gamma^T(t)\theta \qquad (17)\end{aligned}$$

- Identification Algorithm

$$\begin{aligned}\hat{\theta}(t) &= \hat{\theta}(t-1) + K(t)\epsilon(t) \qquad (18)\\ \epsilon(t) &= \dot{\alpha}(t) - \gamma^T(t)\hat{\theta}(t-1) \qquad (19)\\ K(t) &= P(t)\gamma^T(t) \qquad (20)\\ P(t) &= \tfrac{1}{\lambda}\{P(t-1)\\ &\quad - P(t-1)\gamma(t)\gamma^T(t)P(t-1)\\ &\quad /[\lambda + \gamma^T(t)P(t-1)\gamma(t)]\} \qquad (21)\end{aligned}$$

where $\dot{\alpha}$ and $\dot{\alpha}_m$ are real angular velocity and measured one from gyroscope, respectively, and λ is the forgetting factor. θ is the real parameter vector, whereas $\hat{\theta}$ shows the estimated parameters, and K is the adaptation gain.

Note that, in this procedure, since real angular velocity is estimated from odometry, i.e., wheel sensors, it can produce a wrong identification result when disturbances occur at the wheels. In order to avoid this, according to the disturbance condition, this identification algorithm should be properly activated.

In summary, we integrated information from the odometry and gyroscope as shown in Figure 5. When odometry is not valid due to the disturbance, we do not update the parameters of the gyroscope, just use the previous values. Otherwise, the on-line identification procedure will update the parameters of the gyroscope to give more accurate information. The performance of this condition-based identification will be shown in the next section.

5 EXPERIMENTS

In this section, several path-following experiments are carried out in order to compare the accuracy of our method with the conventional ones. To measure an estimation error easily, we build a path shown in Figure 6, of which the

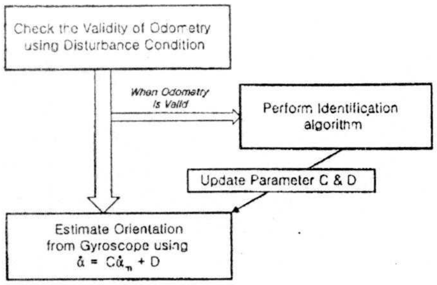

Figure 5: The Estimation of Orientation

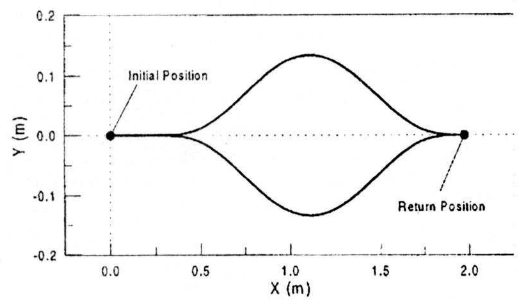

Figure 6: Desired Trajectory

final position and orientation are identical to the initial one. Hence, the difference between the final and initial posture can be considered as a measure of accuracy of the estimation method. In each experiment, the path-following task is repeated five times for the given trajectory so that the effect of error accumulation can be shown distinctively. It takes about 90 seconds to conduct this task and the maximum linear and angular velocity are 0.3 m/s and 40 deg/sec, respectively.

Comparison of Dead-reckoning Methods

The following dead-reckoning methods are compared.

- Method 1 : Odometry only
  - using s_r and s_l
- Method 2 : Odometry with Gyroscope
  - using the conventional off-line identification of the bias voltage
- Method 3 : Odometry with RGI
  - performing the bias voltage identification only
- Method 4 : Odometry with RGI
  - using no front wheel information(s_r, s_l)
- Method 5 : Odometry with RGI
  - using front wheel information (s_r, s_l, s_f,ϕ)
- Method 6 : Odometry with RGI
  - using only steering angle information (s_r, s_l, ϕ)

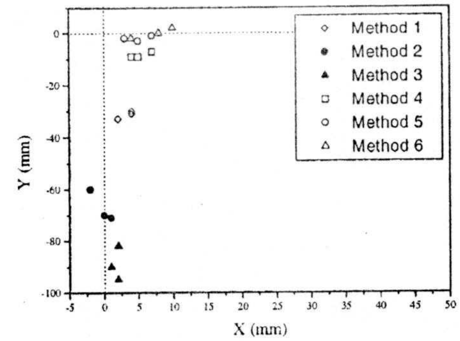

Figure 7: The Errors of Final Position

The first two methods are the conventional ones [3], and, for the remaining methods, we perform real-time gyroscope identification according to the availability of the front wheel information. Since it is impossible to use disturbance condition in Method 4 where no front wheel information is used, we cannot extract precise information from the odometry. In this case we assume the disturbance appears over a short time and perform the RGI routine continuously without any rejection of odometry data. Figure 7 shows the final position error of the mobile robot and Table 2 shows the average position and heading error of each estimation method.

The results of Method 2 and 3 show that the identification algorithm which assumes only the bias voltage varies cannot correctly compensate the uncertainty of gyroscope. Orientation error and position error are clearly smaller in the case using RGI(except Method 3) - the order of magnitude is reduced. These results demonstrate the effectiveness of the proposed RGI method with disturbance condition. We can also find an interesting fact that there is not much difference between methods 5 and 6. Hence, in order to cancel out the uncertain effect of gyroscope, it is enough to use the steering angle information only. In the case of Method 4, the estimation error is larger than those of Method 5 and 6 which use the front wheel sensor(s). In the case when the additional sensor is not available like a differential-drive type WMR, however, it may be a good alternative to use the Method 4.

Table 2: The Average Estimation Errors

Method	Position Error	Heading Error
1	x=3.3mm y=-31.3mm	2.69 deg
2	x=0.3mm y=-67.0mm	4.47 deg
3	x=3.3mm y=-79.0mm	3.71 deg
4	x=5.3mm y=-8.3mm	0.73 deg
5	x=7.3mm y=0.0mm	0.24 deg
6	x=5.0mm y=-2.0mm	0.22 deg

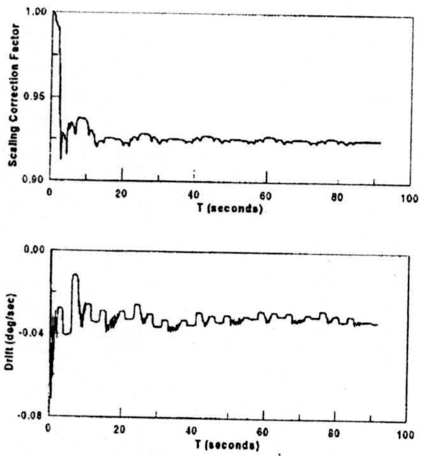

Figure 8: Results of Gyroscope Identification

Figure 8 shows the identified parameters of gyroscope while the mobile robot travels. Clearly, the scaling correction factor of Eq.(3) is not equal to 1 (around 0.925). This means that the linear characteristics of gyroscope cannot be approximated by adjusting only the drift rate as in Eq.(1) and this justifies our proposed output model of the gyroscope.

6 CONCLUSIONS

In this paper, we introduce an enhanced model for gyroscope, which can describe the uncertain scaling factor as well as drift. The conventional drift identification algorithm is shown not to fully compensate the uncertainty of gyroscope by experiments. Using kinematic relation between the wheels, we built a disturbance condition which can recognize whether a disturbance occurs at the wheels or not. We also proposed a condition-based estimation method which can perform both position estimation and on-line gyroscope identification at once while a mobile robot runs using the disturbance condition. Experimental results show the effectiveness of our identification algorithm, it shows that the heading error is within 0.25° after traveling 4 meters path 5 times.

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